CytofRUV: Removing unwanted variation to integrate multiple CyTOF datasets

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Mass cytometry (CyTOF) is a technology that has revolutionised single cell biology. One illuminating application of CyTOF has been in understanding the mechanisms of blood cancer resistance to therapy. Longitudinal studies of clinical cohorts during drug treatment provide a deeper understanding of the molecular changes that underlie sensitivity or resistance to treatment in each patient. However, understanding the biological impact of a cancer drug in such studies necessitates the integration of multiple CyTOF batches. To date, the integration of CyTOF datasets remains a challenge due to technical differences arising in multiple batches. To overcome this limitation, we developed an approach called CytofRUV for analysing multiple CyTOF batches which includes an R-Shiny application with diagnostics plots. CytofRUV can correct for batch effects and integrates data from a large number of patients and conditions across batches, to confidently compare cellular changes and correlate these with clinically relevant outcomes.

Introduction

Mass cytometry or cytometry by Time-Of-Flight (CyTOF) (Bandura et al., 2009) is a high-throughput technology that permits the simultaneous measurement of the expression level of more than 40 proteins in millions of single cells. It uses antibodies which are labelled with heavy metal ion tags to target the proteins of interest, and are in turn detected by time-of-flight mass spectrometry. CyTOF has been a powerful tool for delineating cell subsets in heterogeneous tissues such as blood and tumour, and for correlating single cell differences with biologically relevant outcomes (Levine et al., 2015; Qiu et al., 2011). This capability has been useful in understanding the mechanisms of resistance that develop in certain blood cancers to a new class of anti-cancer drugs, termed BH3 mimetics, in early stage clinical trials of several blood cancers (Agarwal et al., 2019; Blombery et al., 2019). Yet, a major challenge in the field is the high variation in the performance observed in the CyTOF instrument, caused by both differences in instrument calibration and fluctuations in signal strength.

To overcome this challenge, a normalisation method was created to improve the comparability between measurements (Finck et al., 2013). Briefly, the method involves the addition of five types of control beads mixed in with cells, each type tagged with a different heavy metal element, the collection of the control beads throughout the run, and the application of a multiplicative correction at the end of the run. For the multiplicative correction, the algorithm calculates smoothed intensities from each control bead element, estimates a coefficient at each control bead acquisition time-point, and corrects the instrument sensitivity at that specific time-point by computing a unique slope for all the control bead elements, assuming that they vary at similar rates. To extend from control bead events to all cells, the value of the coefficient is linearly interpolated over all time-points of the experiment by assuming that all cells (non-control bead events) have similar slopes to the closest bead time-point. The final normalisation step involves applying the interpolated correction coefficient to all the protein measurements. The use of this normalisation to account for intra-instrument time-drift variation has become common practice, but novel correction procedures are still needed to address all other types of variation between samples between research centers, (see e.g. (Leipold et al., 2018) and within laboratories run on different days (see below).

In this study, a single CyTOF dataset, barcoded sample set or run is referred to as a CyTOF batch. We call the batch effects we seek to remove “unwanted variation”, and their causes include: differential antibody staining across samples within a batch, different batches of reagents, different machines or the inevitable lab differences found in multicentre studies. The ability to accurately distinguish true biological changes from technical artefacts like those just mentioned is critical, and has already been done to an extent for flow cytometry assays (Finak et al., 2016; Maecker et al., 2012).

Two methods have recently been published that aim to achieve consistency between samples across batches which make use of shared reference samples across batches. BatchAdjust (Schuyler et al., 2019) offers methods analogous to the control bead normalisation described above, which include scaling all measurements by ratios of means or medians. With the scaling methods, a factor is computed for each protein and each batch to adjust the measurements on the reference samples replicated across batches. Similar adjustments are

then applied to the samples within a batch to achieve consistency with their reference samples. However technical variation can impact specific cell types differently (Van Gassen, et al., 2019). To address this, CytoNorm (Van Gassen, et al., 2019) uses the clustering algorithm FlowSOM (Van Gassen et al., 2015) to identify cell subpopulations prior to normalisation, and defines a subpopulation-specific goal distribution for the values of each protein measurement using the means of quantiles. Their approach then uses splines to transform the original protein values into new values which have the goal distribution. This method relies on the strong assumption that batch effects do not affect the clusters, and this is examined using coefficients of variation. Both methods were shown to be effective in removing batch to batch variation in the datasets analysed. The observation that batch differences can affect cell subpopulations differently (Van Gassen et al., 2019) suggests that it will not be sufficient to apply a single batch adjustment to the measurements on all cells, as it is being done in BatchAdjust (Schuyler et al., 2019). However, a comparison of the two methods assessing the performance and limitations of each method has not been performed. Additionally, there are no tools or metrics to assess whether the post normalized CyTOF data is more or less consistent across batches, not only at the protein expression level but also at the cell subpopulation level.

In recent years, a class of methods called RUV (Remove Unwanted Variation) has been developed to remove unwanted variation such as batch effects, from high-dimensional genetic and genomic data. They have been applied to microarray (Gagnon-Bartsch & Speed, 2012), RNA-seq (Risso et al., 2014), Nanostring nCounter gene expression (Molania et al., 2019) and single-cell RNA-seq data (Lin et al., 2019). Here, for the first time, we adopt the approach and develop a computational algorithm which permits the integration of data across CyTOF batches. Our method is based on the RUV-III method (Molania et al., 2019) which uses technical replicates and negative control genes to estimate unwanted variation. We applied RUV-III to CyTOF data by exploiting pseudo-replicates to estimate the unwanted variation and remove it. It is implemented in the R package “CytofRUV” and available at the following link: www.github.com/mtrussart/CytofRUV. We begin by examining the batch effects found when comparing CyTOF data from samples replicated across batches. To do so, we built an R-Shiny application that exhibits any batch effects present in such samples using four different diagnostics plots and their associated numerical metrics based on protein expression distributions and clustering results. Then, we compare the unadjusted data with the normalised data using either CytofRUV, BatchAdjust or CytoNorm, all on three different datasets. Our results suggest that not only does CytofRUV does better at removing unwanted variation from measured protein expression, it also makes the distributions of these quantities more uniform across batches, and enhance the detection of biologically important changes embodied in the data across batches.

Results

Batch effects include protein expression differences

A known source of unwanted variation in CyTOF datasets is the time-drift in signal intensity (Finck et al., 2013). However, there can also be variation due to differences across batches in antibody conjugates or other reagents, as well as operators, machines and laboratories. To exhibit some of the batch effects that can arise with CyTOF within one lab, we conducted an experiment using samples replicated across batches. Replicated samples allow us to assess intra-site reproducibility and systematic differences due to technical variation.

We created a dataset based on 24 samples in total, consisting of peripheral blood mononuclear cell (PBMC) samples from 3 patients with chronic lymphocytic leukaemia (CLL) and PBMC from 9 healthy controls (HC), each replicated across two batches of 12 samples (Table 1). All samples were stained with a 31-antibody panel targeting 19 lineage (Table 2) and 12 functional proteins (Table 3) that were previously validated (Teh et al., 2020). After processing the data (Methods), we applied an arcsinh-transformation defined as *arcsinh (intensity/5)* in all that follows.

The first class of diagnostic plots we use are based on the median protein expression. The multi-dimensional scaling (MDS) plot (Fig.1A) computed using median protein expression from all cells in each sample as described in (Crowell HL, 2017; Nowicka et al., 2017), shows the dissimilarities between samples. The first dimension (MDS1) separates the CLL from the HC samples well. The second dimension (MDS2) shows the batch differences, with samples that originate from batch 1 placed at the bottom of the plot and samples from batch 2 at the top of the plot. This distinction clearly reveals that the protein expression measured in the samples is affected by batch. We also carried out hierarchical clustering on the median expression across all cells in the samples of the 19 lineage proteins and 12 functional proteins detected, to highlight the proteins driving the observed clustering of samples (columns) and proteins (rows) in the heatmap (Fig. 1B). As with the MDS plot, a grouping of samples by condition and by batch is observed.

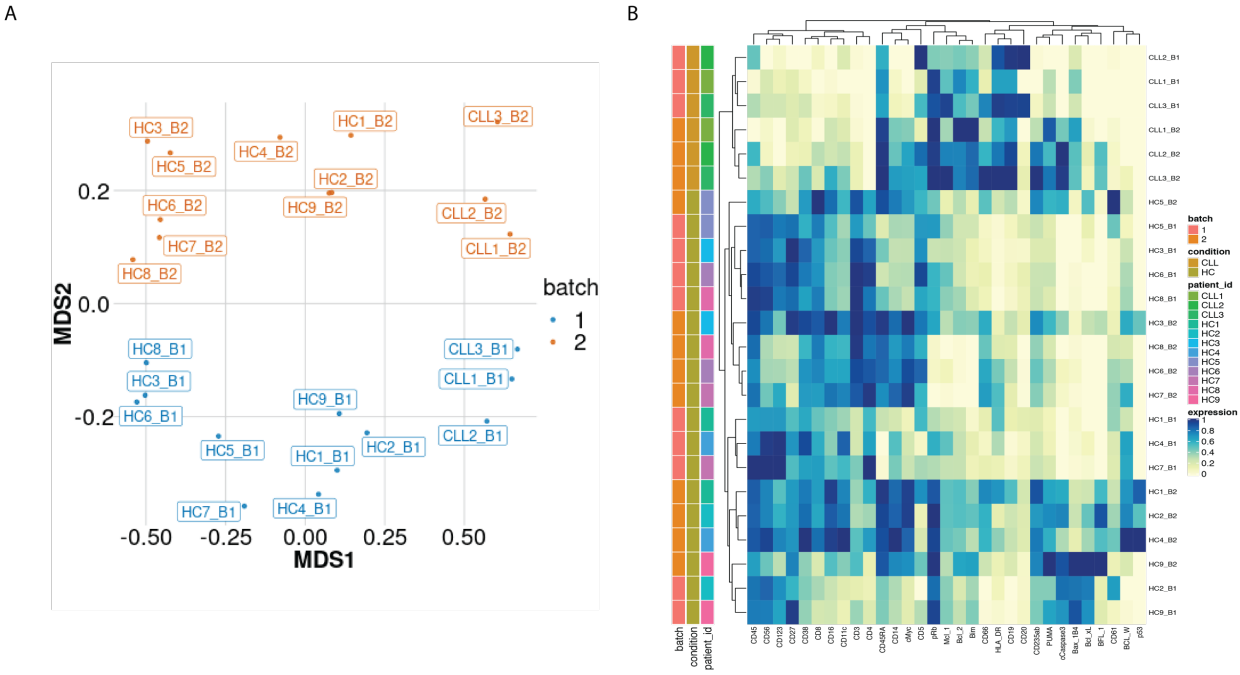


Figure 1: Visualization of batch effects on the median protein expression across batches*. A) Multi-dimensional scaling plot of the 24 samples computed using median protein expression. B) Heatmap of the median protein expression of 19 lineage proteins and 12 functional proteins across all cells measured for each sample in the dataset.*

We next examined the magnitude of the batch-to-batch differences in the distributions of the protein expression across replicates, as our second class of diagnostic plots. We observed that batch effects are not only affecting each protein differently (Supp. Fig 2a) but also each sample differently (Supp. Fig. 2a). To assess the importance of the variation found between samples replicated across batches, we compared them to expected, biologically relevant differences within a single batch. To do this we used here another dataset of a replicated sample from one index CLL patient, and samples from 6 other CLL patients. The one sample from the index CLL patient was replicated across 8 different CyTOF batches, resulting in 8 replicated CLL datasets. We compared the variation in these datasets to that from 6 other CLL patients processed in a single CyTOF batch. We focussed on expression of BCL-2, an archetypal pro-survival protein that is greatly upregulated in CLL cells compared to their normal B cell counterparts, yet still exhibits variation in CLL cells among patients (Majid et al., 2008). We found that the variation in the distributions of the BCL-2 expression from a single sample across batches (Fig. 2A) is comparable to that observed in the BCL-2 expression for the 6 patients at screening from a single CyTOF batch (Fig. 2B). We conclude that batch effects due to unwanted variation can occur in a range comparable to those due to actual biological changes among patients (Fig. 2A-B). An important repercussion in this example is that the impacts of treatments on distinct CLL cellular phenotypes would not be confidently detected without correcting for batch effects.

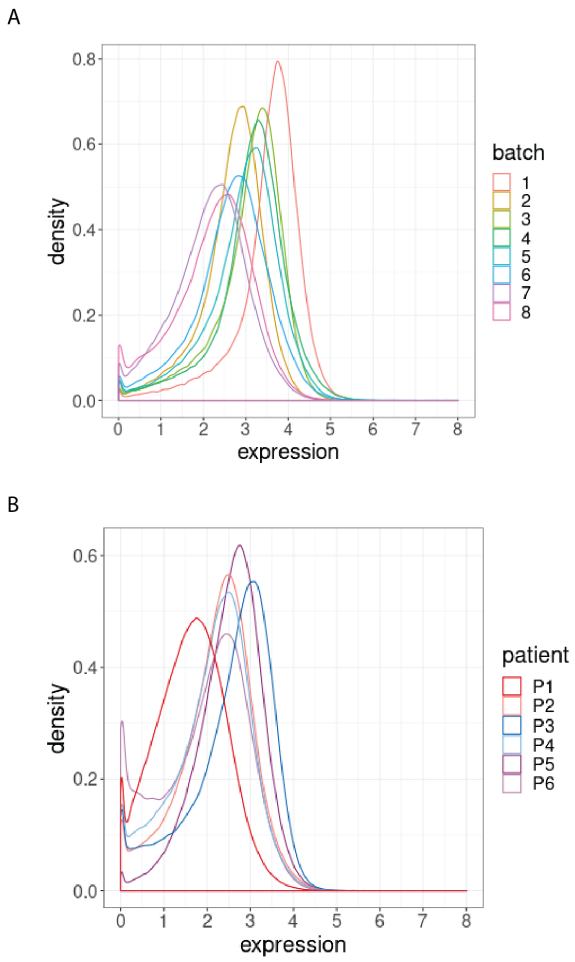


Figure 2: Distribution of BCL-2 expression*. A) Distributions of BCL-2 expression in one sample from one treated CLL cancer patient, replicated across 8 CyTOF batches, coloured by batch. B) Distributions of BCL-2 expression in one sample from each of 6 different CLL cancer patients at screening, processed in a single CyTOF batch, coloured by patient.*

Batch effects can induce differences in cell subpopulation abundances

To assess whether batch effects affect cell subpopulation frequencies, we used our first dataset of samples from 3 CLL patients (CLL) and 9 PBMC healthy controls (HC). We partitioned the entire collection of cells into clusters using FlowSOM as described in (Nowicka et al., 2017), which appeared amongst the fastest and best performing clustering approaches for CyTOF data (Weber & Robinson, 2016). In all 24 samples, we carried out this clustering using the 19 lineage proteins to identify 20 cell subpopulations (Fig. 3A and Supp. Fig. 1). We performed the clustering using different numbers of clusters, and the choice of 20 clusters was determined based on the biological interpretation of the cell subpopulations found. The third class of diagnostic plots we display are based on the clustering results. We used t-Distributed Stochastic Neighbor Embedding (t-SNE) as described in (Crowell HL, 2017; Nowicka et al., 2017) to give a 2D representation of the single-cell data, with the positions of cells reflecting their proximity in high-dimensional space . It was then possible to visualise the impact of batch differences on cell subtypes identification in the datasets by examining the t-SNE plot coloured by cluster (Fig. 3A), which assumed different distributions across the replicate CyTOF runs. Additionally, we highlighted the batch effect by overlaying the

predominant CLL cell subpopulation (cluster 9) coloured by batch (Fig. 3B). The distinct positions of these clusters on the second dimension (t-SNE2) suggested substantial unwanted variation was altering cell population measures across the two batches.

To optimise the dimensionality reduction and visualize the extent to which discrete subsets of cells are separated from each other in the 31-dimensional space, we performed a linear discriminant analysis (LDA) on four subsets of cells: the predominant CLL cell subpopulation (cluster 9) and CD8 killer cell subpopulation (cluster 2) identified in the study from batches 1 and batch 2. The first dimension (LD1) separates the cell types well, while the second dimension (LD2) embodies batch differences: cells that originate from batch 1 are located at the top of the plot while cells from batch 2 are at the bottom of the plot (Fig. 3C).

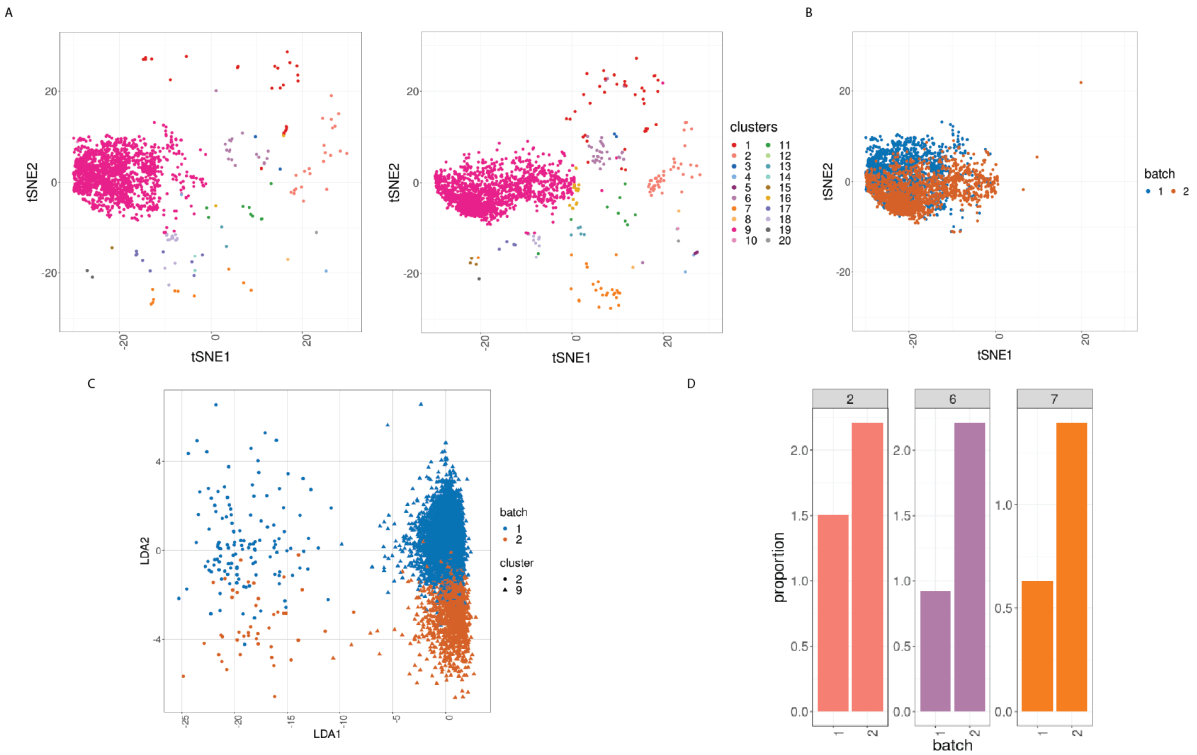


Figure 3: Cell clustering plots show batch effects in cells from the same cancer patient CLL1 sample replicated across 2 CyTOF runs*. A) Cell subpopulation identification. t-SNE plot based on the arcsinh-transformed expression of the 19 lineage proteins in the cells. For display purposes, 2000 cells were randomly selected from each of the samples. Cells are coloured according to the 20 cell subpopulations obtained using FlowSOM clustering stratified by batch 1 (left) or 2 (right) of the corresponding replicated sample. B) Same as in A) selecting only cluster 9 cells but coloured by the batch 1 or 2 of the corresponding replicated sample. C) Linear discriminant analysis applied to data on two cell types from the same sample replicated across 2 batches, with shape indicating cell type and colour indicating batch. D) Clusters proportions. Barplot of the relative abundance (percentage) of the cells in clusters 2, 6 and 7 by batch.*

In CyTOF studies, the analysis of cell subpopulation abundances as well as that of protein expression can be used to identify sets of proteins that are associated with response to a treatment. Comparing the proportions of inferred cell types across different drug treatments highlights the subpopulations that change across experimental conditions. To assess whether

batch differences affect cell subpopulation abundances, we compared the cell subpopulation frequencies across replicates. We detected a noticeable difference in the proportions of CLL cancer cells (cluster 2, cluster 6 and cluster 7) among cells that originate from the batch 1 compared to those from batch 2 (Fig. 3D). Our R-Shiny application can also be used to visualize the cluster proportions across samples, and is our fourth class of diagnostic plot (Fig. 4). Such variation in cell subpopulation abundance is important when batches have markedly different proportions. We need to be able to identify changes in subpopulation abundance which are due to biology and not to unwanted variation between samples.

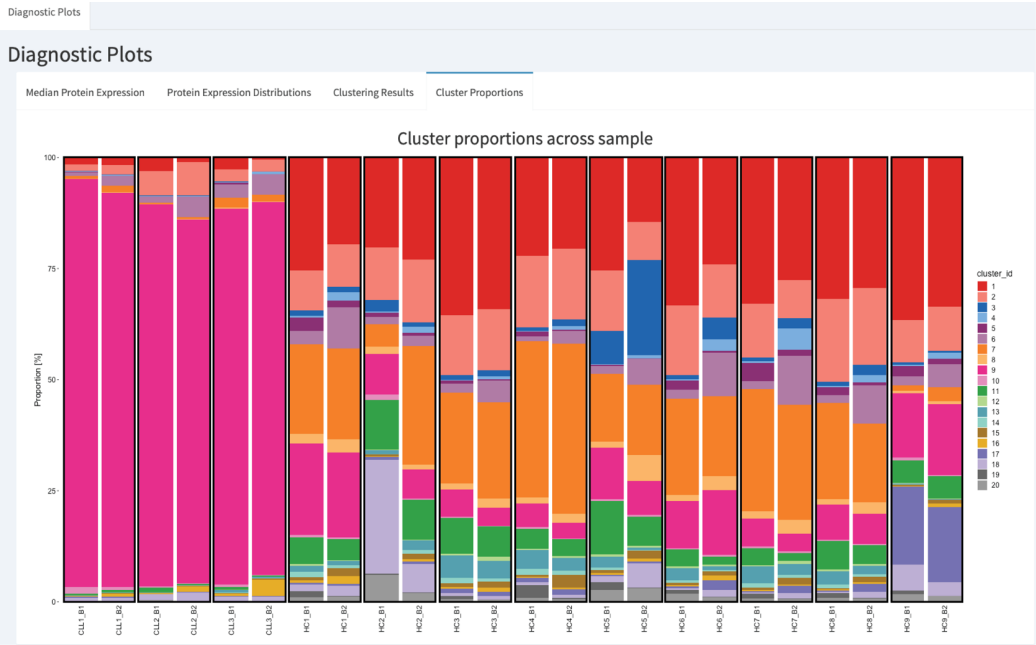


Figure 4: CytofRUV's R-Shiny application for the identification of batch effects in cluster proportions across batches. *All diagnostic plots can be obtained by the user selecting an option at the top left corner by from: Median Protein Expression, Protein Expression Distributions, Clustering Results and Cluster Proportions. The selected option displays barplots of cluster proportions of clusters across samples before normalisation and by conditions CLL or HC on a subsample of the whole dataset. Vertical black boxes contain the same replicated sample across batches 1 and batch2.*

In summary, we examined the reproducibility of samples replicated across batches. To facilitate the identification of batch effects across replicates, we developed an R-Shiny application that produces the four diagnostic plots previously mentioned: Median Protein Expression, Protein Expression Distributions, Clustering Results and Cluster Proportions. We found that batch differences affect not only the protein expression levels, but also the cell subpopulation frequencies. Such differences are problematic in large-scale studies with multiple patients, cell types and treatments, as they compromise the detection of biologically important changes. The integration of datasets from multiple CyTOF batches is therefore an important challenge to be addressed.

Using CytofRUV to remove batch effects in CyTOF data

To integrate data from multiple CyTOF batches, we have developed a normalisation method that removes batch effects in CyTOF data. In order to estimate and adjust for such unwanted variation, CytofRUV exploits the concept of pseudo-replicates (here cells) in the RUV-III

method that has been successfully applied to the Nanostring nCounter gene expression platform (Molania et al., 2019) and to single-cell RNA-seq data (Lin et al., 2019). We cluster using FlowSOM to define several cell subpopulations and we assume that at least one cell subpopulation is shared across the batches in replicated samples. We then consider the cells of subpopulations shared across the batches to be pseudo-replicates (see Methods). To adjust for batch effects, CytofRUV begins by averaging protein values across pseudo-replicates, and then forming residuals. This leads to an estimate of one aspect of the unwanted variation (α) on each protein, which in turn is used to estimate the other aspect (W) of the unwanted variation on each cell. Finally, those estimates are combined into an estimate of the unwanted variation (Wα), and that is subtracted that from the data. The dimension (k) of the unwanted variation also needs to be determined. To find a good value for k, we repeat the analysis with different values of k and then evaluate the quality of each result using our diagnostic plots and the corresponding summary statistics.

We first used CytofRUV on data from the 12 samples replicated across two batches, using two samples as our known replicated reference samples. Specifically, we used HC1 for the HC samples and CLL2 for the CLL samples, defining all cells from those samples in any given cluster to be pseudo-replicates. Assuming that all 20 clusters have cells from CLL1 and HC1 in both batches, any differences in protein expression between cells within the cluster but in different batches will represent unwanted variation. We summarized the performance of our CytofRUV normalisation method on all the CLL samples using three metrics and compare them with the corresponding ones for BatchAdjust (Schuyler et al., 2019) and CytoNorm (Van Gassen et al., 2019).

CytofRUV reduces batch effects from protein expression

To assess the quality of the our CytofRUV normalisation, we first compared the distributions of proteins across the two batches for the designated replicated reference samples. We found that, for all the proteins, these distributions become more similar across batches (Supp. Fig. 2a, Supp. Fig. 2b). We also observed a decrease in the batch effects both in the linear discriminant analysis and on the t-SNE plots (Supp. Fig. 3). To quantify the batch differences between these pairs of distributions, we computed the Earth Movers Distance (EMD) as described in (Van Gassen et al., 2019) for all the proteins and all CLL and HC samples for both the original dataset and the normalized datasets (Fig. 5A and 5D). For only the CytofRUV normalisation, we also computed the EMD by cluster for all proteins to assess the reduction in batch differences within cell subpopulations compared to the raw data, where batch effects are affecting protein distributions within cell subpopulations differently (Supp. Fig. 4). For all CLL samples, CytofRUV gave the lowest EMD for all values of k = 5,10 and 15, not only compared to the raw data but also compared to both BatchAdjust and CytoNorm (Fig. 5A). Similarly, CytofRUV also gave the lowest EMD for 7 out of the 9 HC samples compared to both BatchAdjust and CytoNorm (Fig. 5D).

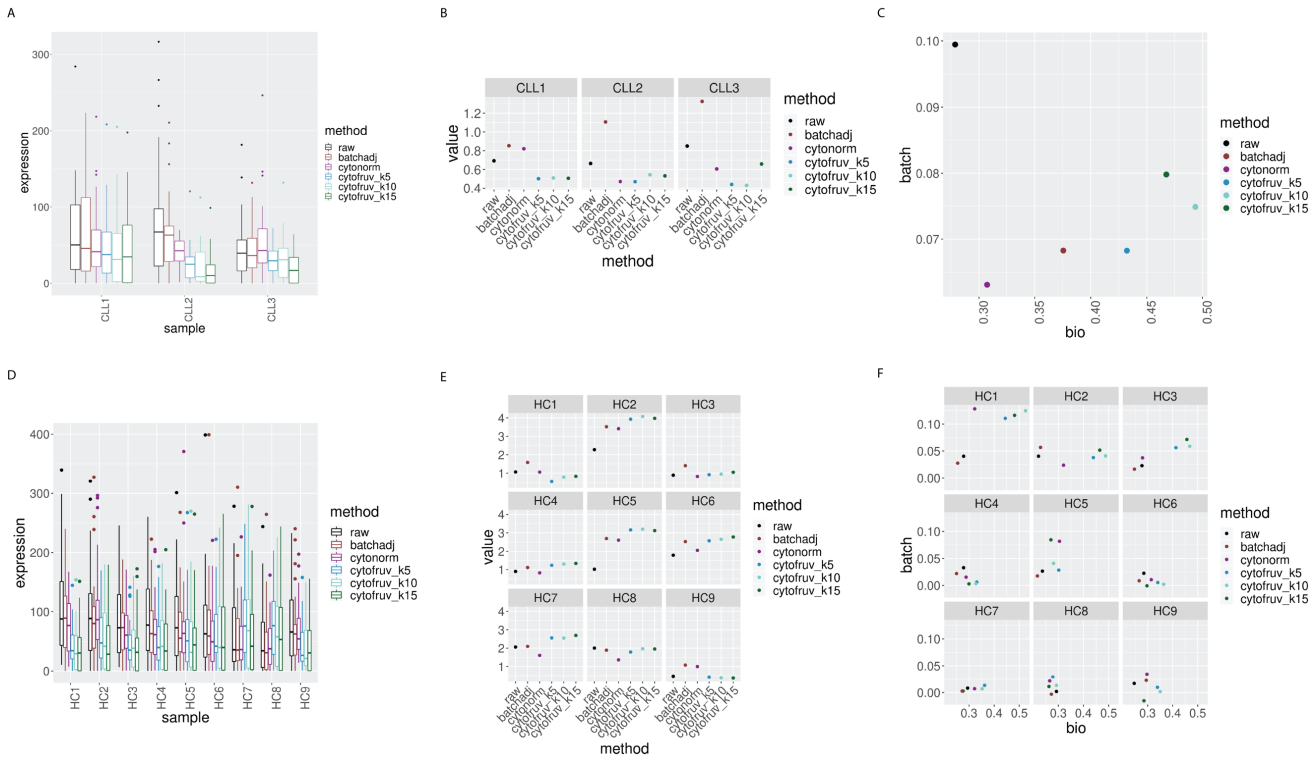


Figure 5: Metrics to assess the effectiveness of the normalisation methods*. In all panels, the colour indicates either the raw data or the method used for normalisation. A) Boxplots of the Earth Movers Distances (EMD) between paired protein expression distributions across batches for each CLL sample. B) Hellinger distances between paired cell subpopulation proportions across batches for each CLL sample. C) Mean silhouette scores computed for all CLL samples on the cell subpopulation types (bio) on the x-axis and on batch (batch) on the y-axis. D) Same as A) for the HC samples. E) Same as B) for the HC samples. F) Silhouette scores computed for all HC samples on the cell subpopulation types (bio) on the x-axis and on batch (batch) on the y-axis.*

CytofRUV makes the cell subpopulation proportions more consistent across batches

The proportions of the different cell subpopulations in replicates in different batches should be consistent. This consistency among the replicates ensures that a differential analysis of their abundances will confidently detect robust cellular changes across experimental conditions. To assess how well CytofRUV corrects for differences in subpopulation proportions across batches, we computed the Hellinger distance (see Methods) between the paired cluster proportions of all replicated samples. For the HC samples, CytofNorm gave the lowest Hellinger distances for 4 samples out of 9 compared to both CytofRUV and BatchAdjust. Two remaining samples are the ones where CytofRUV is able to make those proportions more consistent across replicates (Fig. 5E). For all the CLL samples, the lowest Hellinger distances are found for the normalisation with CytofRUV methods k=5 (Fig. 5C). CytofRUV is able to adjust the cell subpopulation proportions in the CLL samples and make them consistent across replicates to a greater extent than is achieved by BatchAdjust or CytoNorm.

Effective removal of unwanted variation leads to a better separation of cell subpopulations
To evaluate whether CytofRUV not only removes batch effects but preserves biology, we compare the cell-to-cell variation within cell subpopulations in relation to between subpopulations. We do this by computing *Silhouette* scores (see Methods), which are a combined measure of the degree of separation of cells within subpopulations and that between subpopulations. We compute two silhouette scores $s_{biology}$ and s_{batch}, based on the cell subpopulations defined by the clusters, and batch grouping, respectively. A normalisation method that successfully removes batch effects should lead to adjusted data with a small s_{batch} score, while one which preserves or enhances the biology should have high value of $s_{biology}$, at least as high as that before adjustment. To assess this aspect of the performance of normalisation methods, we combine the $s_{biology}$ for cell subpopulations with s_{batch} for the batches in a single plot (Fig. 5C, 5F). When the raw data is found at the bottom left corner of the plot and a normalisation method is found at the top right corner of the plot, this indicates that the method has successfully removed batch effects and preserved or enhanced the biology. According to the mean silhouette scores of the CLL samples (Fig. 5C), CytofRUV with k=5 gives the best results, not only enhancing the biology i.e. cell sub-type definition across replicates (also on t-SNE plots Supp. Fig. 3), but also removing the batch effects. Using CytofRUV with k=5 for the HC samples, we also obtained a higher $s_{biology}$ for 6 out of the 9 HC samples (Fig. 5F).

CytofRUV removes batch effects across multiple batches in two other datasets
To expand our analysis, we also tested all methods on two other datasets containing replicate reference samples across multiple batches, taken from those used in (Schuyler et al., 2019) and in CytoNorm (Van Gassen et al., 2019).

The first dataset (Schuyler et al., 2019) is from peripheral whole blood samples from a single healthy donor, processed at one time to include unstimulated and LPS+R848- stimulated conditions, and aliquoted into 12 batches. We carried out the normalisation of all samples using BatchAdjust as explained in (Schuyler et al., 2019). For CytofRUV and CytoNorm, we used all the stimulated samples as replicated reference samples and identified 20 cell subpopulations with FlowSOM. CytofRUV used all clusters to define pseudo-replicates.

Our R-Shiny application can also be used to assess the ability of a normalisation method to correct for batch effects. Using our fourth diagnostic plot, we can visualize the ability of CytofRUV with k=10 to remove batch effect in cluster proportions across 12 batches (Fig. 6C) compared to that in the raw data (Fig. 6A). We also summarized the performance of all three methods using the same three metrics (Supp. Fig. 5). Again, we observed the ability of CytoNorm to correct for differences in subpopulation proportions in both stimulated (Supp. Fig. 5B) and unstimulated samples (Supp. Fig. 5E). Likewise, we confirmed that, overall, CytofRUV gave lower EMD for both the stimulated (Supp. Fig. 5A) and unstimulated samples (Supp. Fig. 5D), and improved silhouette scores (Supp. Fig. 5C) compared to the two other methods.

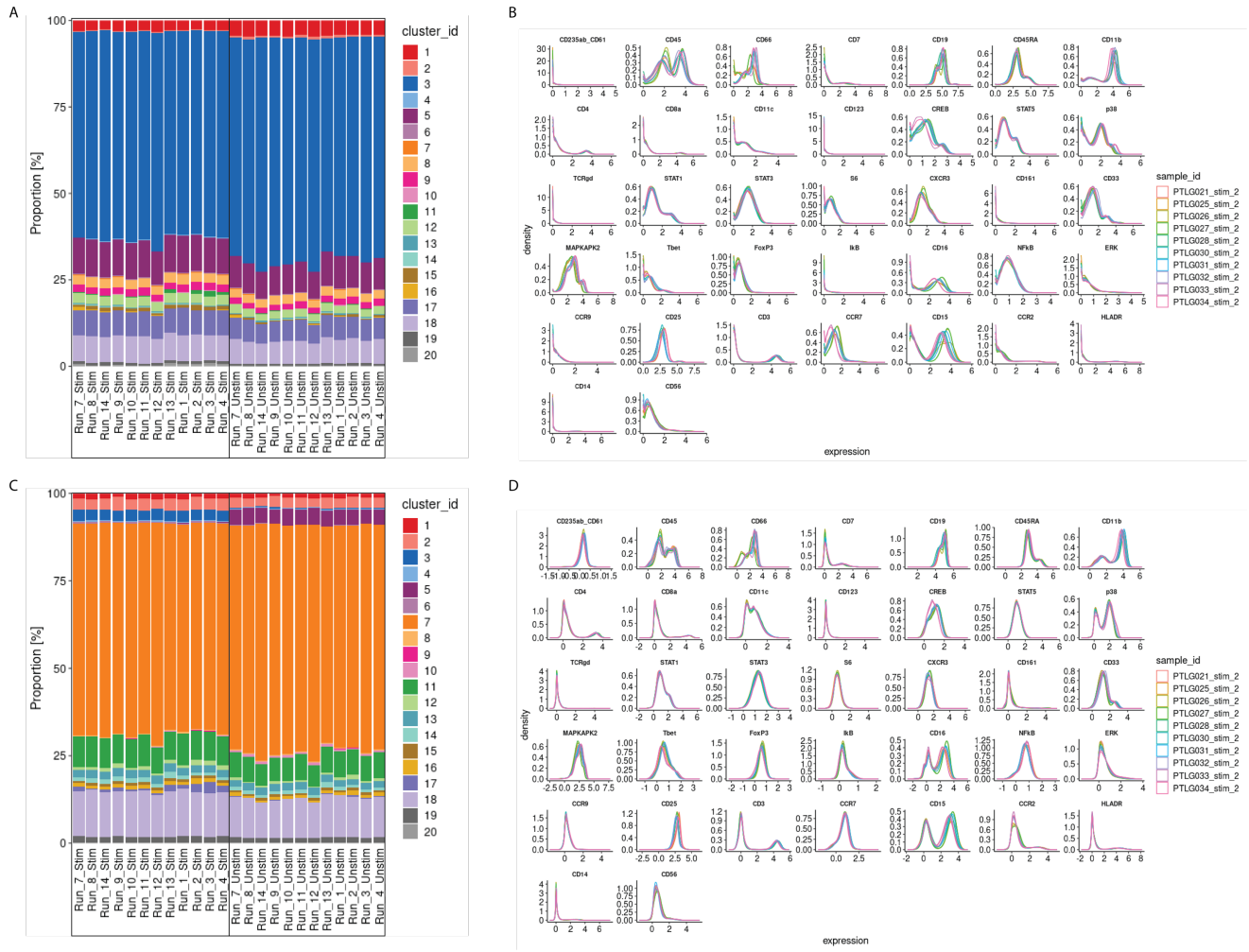


Figure 6: CytofRUV performance on two other datasets with multiple batches*. A) Barplot of proportions of clusters across 28 samples from the BatchAdjust dataset (Schuyler et al., 2019) before normalisation, by samples and coloured by cluster. Vertical black boxes contain the same sample (Stimulated or Unstimulated) replicated across 14 batches. B) Protein expression distribution from the CytoNorm dataset (Van Gassen et al., 2019) before normalisation of all cells from the stimulated samples across 10 batches and coloured by batch. C) Same as A) but after CytofRUV normalisation with k=10. D) Same as B) but after CytofRUV normalisation with k=5.*

The second dataset (Van Gassen et al., 2019) comes from the FlowRepository FR-FCM-Z247 which is the validation cohort of an immunoprofiling study of women during pregnancy used in CytoNorm (Van Gassen et al., 2019). The samples we analyse come from the blood of one healthy donor which was replicated across 10 separately barcoded plates (i.e. batches). Each batch contained unstimulated cells and cells stimulated with both Interferon α (IFNα) and Lipopolysaccharide (LPS). Each stimulated and unstimulated sample was duplicated (referred to as sample 1 and sample 2), giving four samples per plate. To assess the limitations of the three normalisation methods, we carried out two analyses. The first normalisation was only carried out on samples 2 using the stimulated samples 2 as replicate reference samples, while the second normalisation was done on samples 1 and 2 using both the stimulated and unstimulated samples 1 as reference samples. We performed CytoNorm as explained in (Van

Gassen et al., 2019) and identified 25 cell subpopulations with FlowSOM and we used all clusters to define pseudo-replicates for CytofRUV.

For the first normalisation using only the stimulated samples as replicate reference samples, CytoRUV gives lower EMD for both the stimulated and the unstimulated samples when compared with BatchAdjust and CytoNorm (Supp. Fig. 6A, 6C). CytoNorm corrects some differences in subpopulation proportions only in stimulated samples (Supp. Fig. 6B). However, according to the Hellinger distance and silhouette scores, the unstimulated samples still have batch effects after normalisation by all three methods. (Supp. Fig. 6C, 6E).
In our second normalisation, when using both stimulated and unstimulated samples 1 as reference samples, lower Hellinger distances are found on both unstimulated and stimulated samples 2 for CytofRUV and better silhouette scores for CytoNorm (Supp. Fig. 7B, 7E, 7C). Using our second class of diagnostic plots, we observe that CytofRUV with k=5 effectively eliminates batch differences from protein expression across the 10 batches (Fig. 6B) compared to that in the raw data (Fig. 6D). It also gives the lowest EMD (Supp. Fig. 7A, 7D).

Discussion

We have developed a new computational approach for analysing multiple CyTOF batches implemented in the CytofRUV R package. We showed how CytofRUV can reduce batch effects in three different datasets across multiple batches. Our method allows pooling of data from a large number of patients and conditions run across multiple batches, thereby enabling the integration of multiple CyTOF datasets.

Our approach adapts the RUV-III procedure to CyTOF by exploiting pseudo-replicates. We began by examining the batch effects found in CyTOF by comparing data from samples replicated across batches. To do this, we build an R-Shiny interface that highlights the presence of any batch effects in replicated samples using four different diagnostics plots: Median Protein Expression, Protein Expression Distributions, Clustering Results and Cluster Proportions. Finally, we compare CytofRUV with the two recently developed methods, BatchAdjust and CytoNorm, using three different datasets. Our results suggest that not only does CytofRUV frequently do better at removing unwanted variation in measured protein expression, making the distributions of these quantities more uniform across batches, but it also enhances the detection of biologically important differences embodied in the data across batches.

Using replicated samples to assess intra-site reproducibility and differences due to technical variation, we first showed how batch effects differences in protein expression in CyTOF datasets consisting of several CyTOF batches are comparable to biologically relevant differences within a single batch. In that context, confidently detecting of the impact of diverse treatments on distinct CLL cellular phenotypes would not be possible without correcting for such batch effects.

We developed an interactive R-Shiny application that exhibits batch effects in CyTOF studies. Different diagnostic plots can be selected by the user to display any batch effects on CyTOF data before and after normalisation.

We showed that not only are batch effects found in individual protein expression values which was also found in (Schuyler et al., 2019), but also that batch differences affect samples differently. We observed the impact of batch differences on cell subtypes identification and how protein distributions are affected differently within subpopulation, something that was also found by (Van Gassen et al., 2019). This suggest that it will not be sufficient to apply a single batch adjustment to the measurements on all cells, as is performed in BatchAdjust (Schuyler et al., 2019). We also noticed changes in the cell subpopulations abundances across batches.

RUV-III has been successfully applied to the Nanostring nCounter gene expression platform (Molania et al., 2019) and to single-cell RNA-seq data (Lin et al., 2019). Here, we adapted RUV-III to CyTOF data using as pseudo-replicates the subpopulation cells in the different batches, and taking the collection of all protein expression values as "negative controls." We refer to the section "Selection of negative control genes" (Molania et al., 2019) for this last point. Here, as there and in other contexts, before/after normalisation comparisons indicate that this can be effective. Our method is adaptable and flexible in that it allows the user to select different normalisations: it can be implemented for one or several replicated reference samples, it can also normalize specific clusters or all clusters, and the dimension (k) of the unwanted variation can vary. In all cases, the user can visualise the diagnostics plots to assess the effectiveness of their normalisation.

To assess the abilities of CytofRUV, BatchAdjust and CytoNorm to remove batch effects, we computed three statistical metrics. We first compared the distributions of proteins across batches for replicated samples using EMD. Second, to assess how well each method corrects for differences in subpopulation proportions across batches, we computed the Hellinger distance between the paired subpopulation proportions of all replicated samples. Finally, to assess whether each method not only removes batch effects but preserves the biology, we computed silhouette scores that quantify the cell-to-cell variation within cell subpopulations in relation to that between subpopulations.

Overall, CytofRUV had the best capability to make proteins expression distributions more similar across batches. When compared with BatchAdjust and CytoNorm on different datasets it has the lowest EMD for all proteins for most samples. We further saw that batch differences are reduced within cell subpopulations by computing EMD by cluster for all proteins. We also saw CytoNorm's ability to correct for differences in subpopulation proportions as well as CytofRUV. Silhouette scores also indicate that in most of our analyses CytofRUV not only removes the batch effects but also improves biological accuracy of the cell subpopulations. As previously mentioned for CytoNorm, and as we also observed for CytofRUV, in order to remove batch effects from all samples, it might be necessary to include more than one set of replicated references samples in the batch, in particular including samples that are similar to each of the main types of samples.

One limitation of our method is that CytofRUV does rely on the assumption that at least one cell subpopulation is shared across the batches that would be used as our pseudo-replicates. In experiments where large batch effects occur and no cell subpopulation is shared between batches, our method would not be applicable.

In summary, we proposed here a computational algorithm called CytofRUV that effectively enables batch effect reduction in mass cytometry with an adaptable normalisation method to detect heterogeneity of cellular responses across large-scale studies with multiple patients, cell types and conditions (e.g. treatment).

Methods

CytofRUV

To remove the unwanted variation across multiple datasets and batches, we used fastRUVIII as previously described (Molania et al., 2019; Lin et al., 2019). Briefly, the data is first standardized before being fitted to the RUVIII model underlying all RUV analyses:

$$Y_{ij} = X_i\beta_j + W_i\alpha_j + \varepsilon_{ij}$$

Here, Y_{ij} is the standardized expression value (arcsinh(intensity/5)) for protein *j* in a cell *i* with $i = 1, \dots, m \; and \; j = 1, \dots, n$, of *m* cells and *n* proteins. The standardisation is to have zero mean and unit standard deviation across all cells for all protein measurements.
X_i represents the factors of interest for the sample giving cell *i*. W_i represents the unwanted factors for that cell. The dimension of the unwanted factors is being denoted by k. α_j represents the coefficient of W_i for protein j in a cell i and ε_{ij} is noise, typically $\varepsilon_{ij} \sim N(0, \sigma_j^2)$.

The data is normalised in six steps. First, *all* the data is clustered, typically using FlowSOM, although other clustering methods can be used. Second, group of cells are defined to be pseudo-replicates if they belong to the same subpopulation (i.e. cluster) but are in different batches, which can be done either on specific clusters or on all clusters. Third, cell-level residuals are computed by averaging all the protein measurements across those pseudo-replicates, and subtracting these averages from each measurement on each cell. In essence, differences of measurements on pseudo-replicates are considered as unwanted variation. The quantities α_j are then estimated from the singular value decomposition (SVD) of the *m x n* matrix of these residuals. Next the k-vectors of W_i for the cells are then estimated using *all* proteins as "negative controls". Finally, the estimates of W_i and α_j are multiplied to get an estimate of $W_i\alpha_j$, which is then subtracted from the Y_{ij} to get the final adjusted data. Full details and a discussion of key issues can be found in (Lin et al., 2019; Molania et al., 2019).

BatchAdjust

For all the datasets, BatchAdjust was performed using the R code and usage instructions as described in (Schuyler et al., 2019). We used the option of scaling the 95th percentiles with no transformation applied to the data before adjustment.

CytoNorm

CytoNorm was performed as described in (Van Gassen et al., 2019) following the two steps provided in the R library CytoNorm to normalize the data.

Earth Movers Distance

To quantify the similarity of protein expression distributions across batches, we computed the Earth Movers Distance, also called the Wasserstein metric, as described in (Van Gassen et al., 2019). Briefly, the data is binned and we computed the pairwise EMDs across batches for the distribution of every protein over all cells as well as over the cells in each cluster. This was done for both the original dataset and the normalized datasets.

Hellinger Distance

To quantify the differences between cluster proportions across batches, we computed the Hellinger distances between the proportions found in samples replicated across different

batches. This distance is defined for two probability distributions $p = (p_i)$ and $q = (q_i)$ by $H(p,q)$, where $H(p,q)^2 = \frac{1}{2}\sum_{i=1}^{n}(\sqrt{p_i} - \sqrt{q_i})^2$.
We computed these distances for both the original and the normalized datasets.

Silhouette scores

To assess the extent to which the data is grouped based on the batch effects as opposed to biological signals, we computed batch and biology silhouette scores. Given a partitioning of all cells into groups, if a_i denote the average Euclidean of the protein expression between the cell *i* and all other cells in the group to which cell *i* is assigned, and b_i is the minimum of the average distance between the cell *i* and any cells in other groups not containing cell *i*, then the silhouette coefficient of cell *i* is calculated as

$$\mathrm{s}(i) = \frac{b_i - a_i}{\max\{b_i, a_i\}}$$

The average of the silhouette values across cells using a particular grouping is called the silhouette score for that grouping. In this way, we computed the silhouette score s_{batch} based on the batches as groups and the silhouette score $s_{biology}$ based on the grouping of the cells by subpopulation (i.e. clusters).

R package CytofRUV

Our algorithm is implemented in the R package "CytofRUV" and is available at: www.github.com/mtrussart/CytofRUV. Installation and R code usage instructions for both the R package and the R-Shiny application can be found on the GitHub page. Users are required to provide: the FCS files from all samples in the study, a metadata file containing the details of each sample and a panel file containing the details of all proteins used in the study. The R-Shiny application allows the user to explore the data and identify batch effects across replicates using the diagnostic plots previously mentioned: Median Protein Expression, Protein Expression Distributions, Clustering Results and Cluster Proportions using samples replicated across batches. It can be explored on all the data or on a subsample of the data. The normalize_data function allow the user to adjust for batch effects with parameter settings for the CytofRUV algorithm, such as which replicated samples to use and the value of k. The pipeline and scripts used to generate the results described in this manuscript is also available in the supplementary data.

PBMC samples from patient and healthy donor

Blood was obtained from healthy donors (via the Victorian Donor Blood Registry) and CLL patients (via the Royal Melbourne Hospital, Australia). All patients consented under Melbourne Health HREC 2016.305 and samples were analysed under HREC 2016.066. PBMCs were isolated using standard Ficoll-based methods and cryopreserved.

Mass cytometry

Cells were thawed and stained for viability with cisplatin. Cells were then fixed with paraformaldehyde (PFA: Electron Microscopy Sciences, Hatfield, PA, USA) to a final concentration of 1.6% for 10 minutes at room temperature. Cells were pelleted and washed once with cell staining medium (CSM, PBS with 0.5% BSA and 0.02% sodium azide) to remove residual PFA and stored at -80°C.

Cells were barcoded using 20-plex palladium barcoding according to manufacturer's instructions (Fluidigm, South San Francisco, CA, USA). Following barcoding, cells were pelleted and washed once with cell staining medium (PBS with 0.5% BSA and 0.02% sodium azide) to remove residual PFA. Cells were stained with CD16/CD32 for 10 minutes and surface antibodies (Table 2) for 30 min at room temperature. Cells were permeabilized with 4°C methanol for 10 min. Cells were washed three times with CSM and stained with intracellular antibodies (Table 2) for 30 min at room temperature. Cells were washed with CSM, then stained with 125 nm ^{191}Ir/^{193}Ir DNA intercalator (Fluidigm, South San Francisco, CA, USA) in PBS with 1.6% PFA at 4°C overnight. Cells were washed once with CSM, washed three times with double-distilled water and filtered to remove aggregates and resuspended with EQ normalisation beads immediately before analysis using a Helios mass cytometer (Fluidigm, South San Francisco, CA, USA). Throughout the analysis, cells were maintained at 4°C and introduced at a constant rate of ~300 cells/sec.

Processing data for mass cytometry

Data concatenation, normalisation and debarcoding are done using the R Catalyst package merging the two batches (RUV_1B and RUV3B) when applying the Finck normalisation. The R script used to generate this preprocessing (Debarcoding_normalisation.R) is also available in the supplementary data.

Flow Repository

The fcs files from this study will be available at flow repository ID FR-FCM-Z2L2.

Acknowledgments

MT and TPS were supported by NHMRC Program Grant 1054618. DHDG is supported by a NHMRC Senior Research Fellowship (1158024), a Cancer Council of Victoria Grant-in-aid (1146518) and support from the Victorian Comprehensive Cancer Centre. CET is supported by an Australian NHMRC Early Career Fellowship (1089072)
We are grateful to Dr MaryAnn Anderson and Prof Andrew Roberts for the provision of patient material.
This work was performed in part at the Materials Characterisation and Fabrication Platform (MCFP) at the University of Melbourne and the Victorian Node of the Australian National Fabrication Facility (ANFF).

Tables

Sample Id	Condition	Patient Id	Batch
HC1_B1	HC	VBDR996	1
HC2_B1	HC	VBDR1089	1
HC3_B1	HC	VBDR1090	1
HC4_B1	HC	VDBR1098	1
HC5_B1	HC	VDBR1108	1
HC6_B1	HC	VDBR1103	1
HC7_B1	HC	VDBR1105	1
HC8_B1	HC	VDBR1107	1
HC9_B1	HC	VBDR1111	1
CLL1_B1	CLL	DG33-01	1
CLL2_B1	CLL	DG23-01	1
CLL3_B1	CLL	DG27-01	1
HC1_B2	HC	VBDR996	2
HC2_B2	HC	VBDR1089	2
HC3_B2	HC	VBDR1090	2
HC4_B2	HC	VDBR1098	2
HC5_B2	HC	VDBR1108	2
HC6_B2	HC	VDBR1103	2
HC7_B2	HC	VDBR1105	2
HC8_B2	HC	VDBR1107	2
HC9_B2	HC	VBDR1111	2
CLL1_B2	CLL	DG33-01	2
CLL2_B2	CLL	DG23-01	2
CLL3_B2	CLL	DG27-01	2

***Table 1**: **Samples descriptions.** The first column indicates the sample id, the second the patient condition, either healthy controls (HC) or chronic lymphocytic leukaemia (CLL), the third column indicates the patient id and the last indicates the batch number, 1 or 2.*

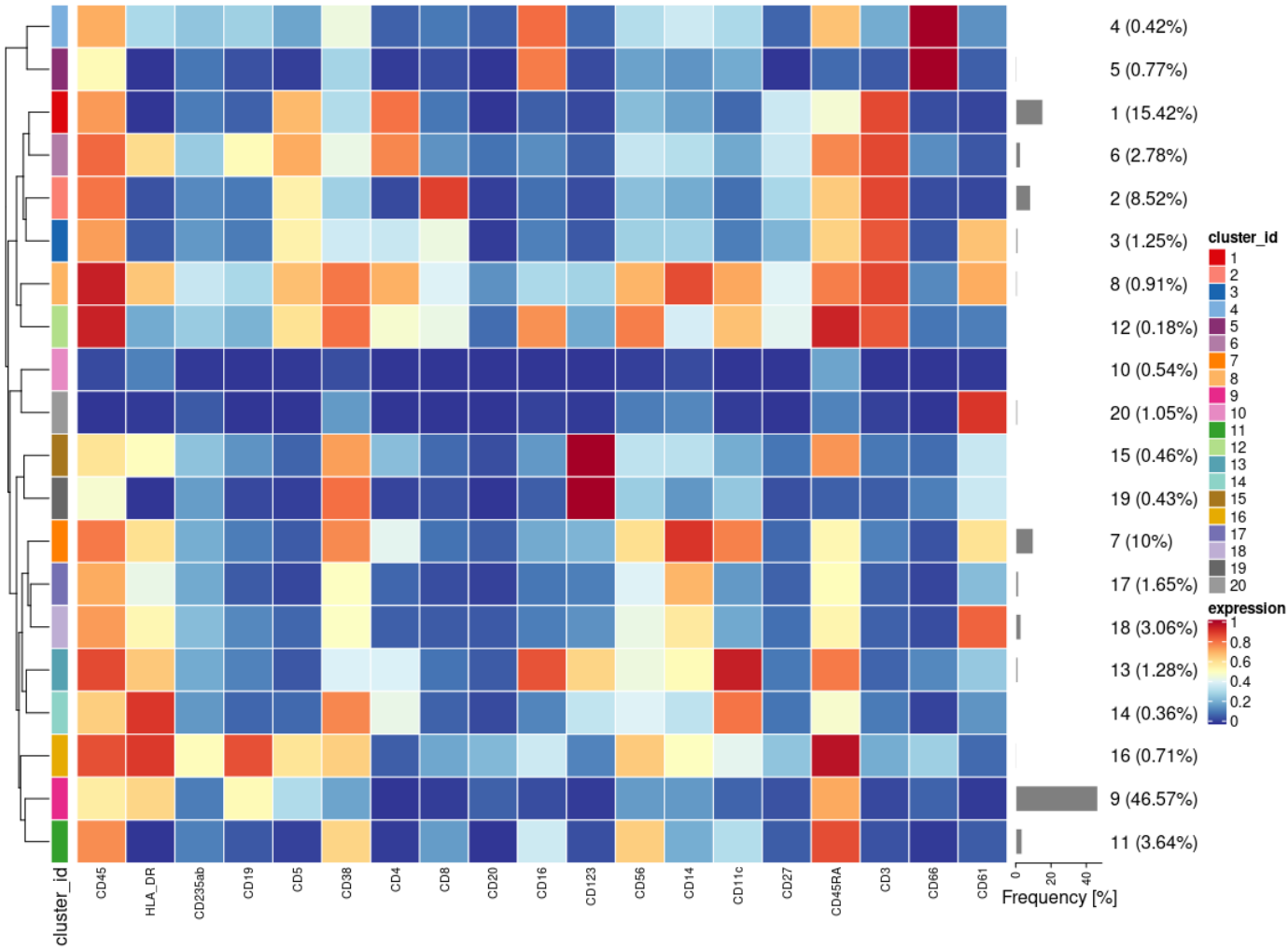
	Metal	Lineage (surface) protein antibody	Clone	Vendor
1	89 Y	CD45	HI30	BioLegend
2	115 In	HLA-DR	L243	BioLegend
3	140 Ce	CD27	M-T271	BioLegend
4	141 Pr	CD235a/b	HIR2	BioLegend
5	142 Nd	CD19	HIB19	BioLegend
6	143 Nd	CD5	UCHT2	BioLegend
7	144 Nd	CD38	HIT2	BioLegend
8	145 Nd	CD4	RPA-T4	BioLegend
9	146 Nd	CD8	RPA-T8	BioLegend
10	147 Sm	CD20	H1	BD
11	148 Nd	CD16	3G8	BioLegend
12	151 Eu	CD123	6H6	BioLegend
13	155 Gd	CD56	B159	BioLegend
14	156 Gd	CD14	HCD56	BioLegend
15	159 Tb	CD11c	Bu15	BioLegend
16	169 Tm	CD45RA	HI100	BioLegend
17	170 Er	CD3	UCHT1	BioLegend
18	171 Yb	CD66	CD66a-B1.1	DVS
19	209 Bi	CD61	VI-PL2	DVS

***Table 2**: **Lineage surface proteins selected.** The first column indicates the transition element isotope (mass number, element name), the second column indicates the antigen selected and the last two columns indicates the clone name and vendor.*

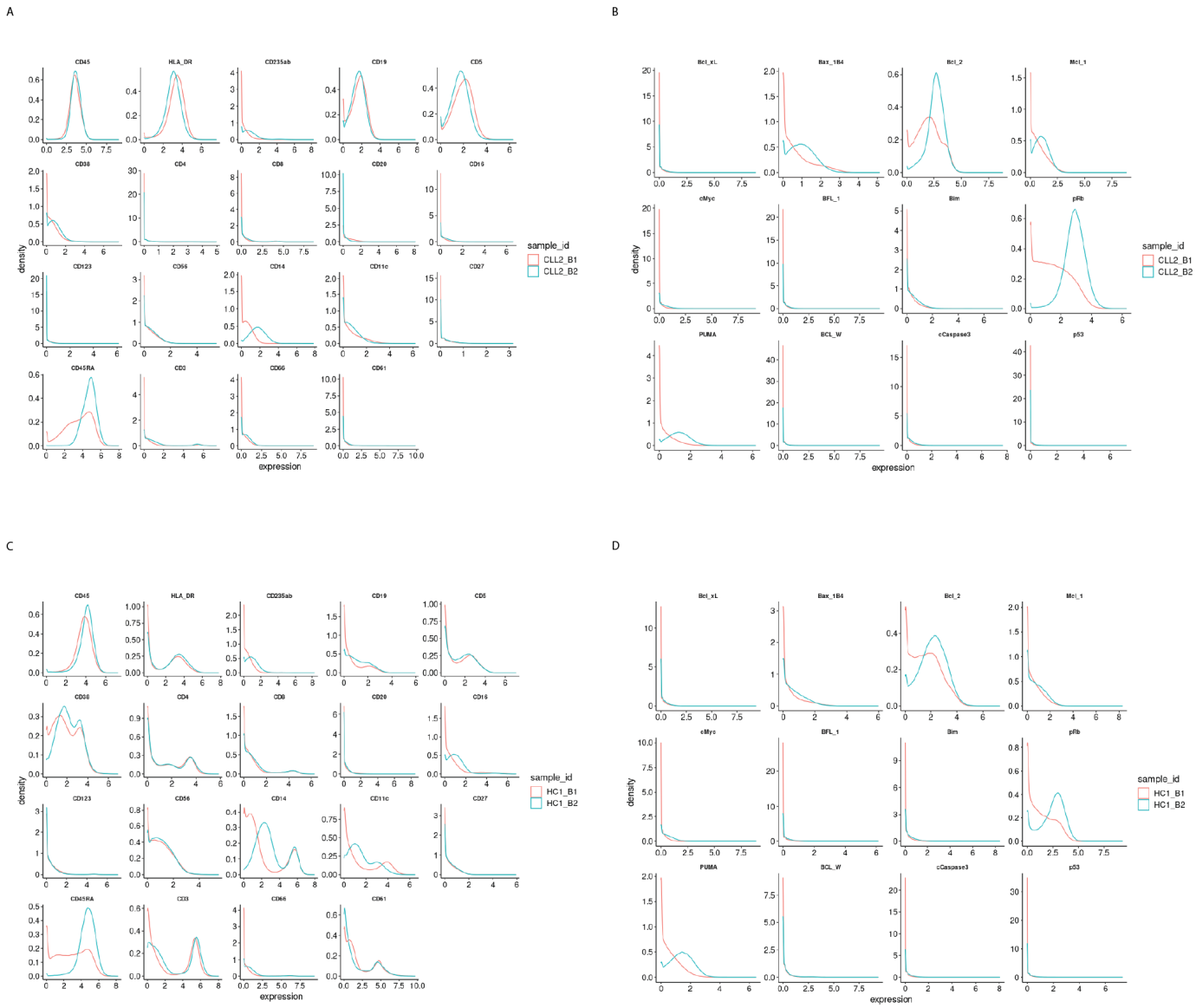
	Metal	Functional (intracellular) protein antibody	Clone	Vendor
1	140 Ce	BAK	7D10	WEHI
2	153 Eu	Bcl-xL	E18	Abcam
3	154 Sm	Bax	1B4	WEHI
4	157 Gd	Bcl-2	100	WEHI
5	160 Gd	Mcl-1	Y37	Abcam
6	161 Dy	cMyc	D84C12	CST
7	163 Dy	BFL-1	SP435	Abcam
8	165 Ho	Bim	3C5	WEHI
9	166 Er	pRb [S807/811]	J112-906	BD
10	172 Yb	BCLW	16H12	WEHI
11	173 Yb	cCaspase3	C92-605	BD
12	174 Yb	p53	7F5	CST

***Table 3**: **Set of intracellular functional proteins selected.** The first column transition element isotope (mass number, element name), the second column indicates the antigen selected and the last two columns indicates the clone name and vendor.*

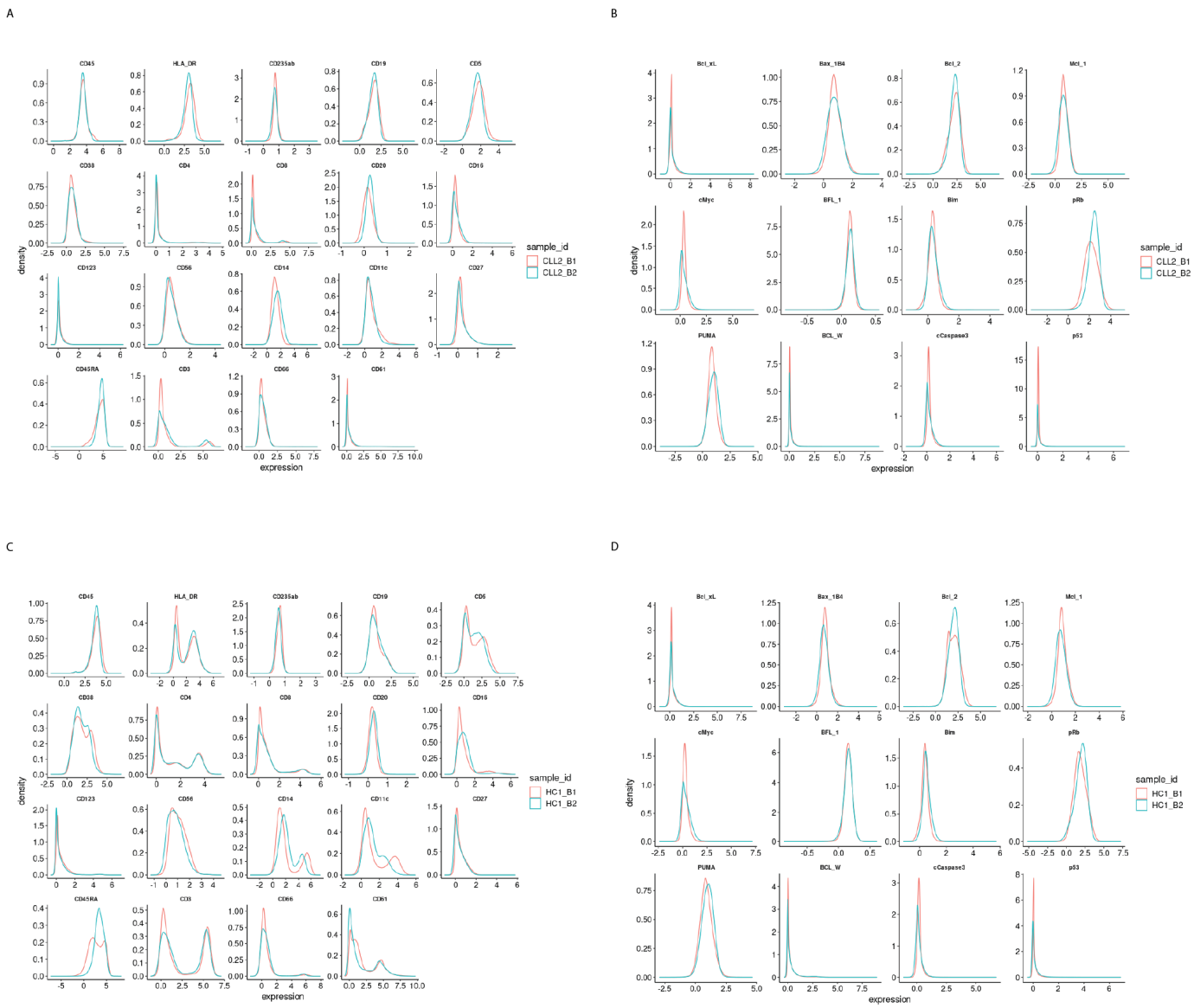
Supplementary Figures:



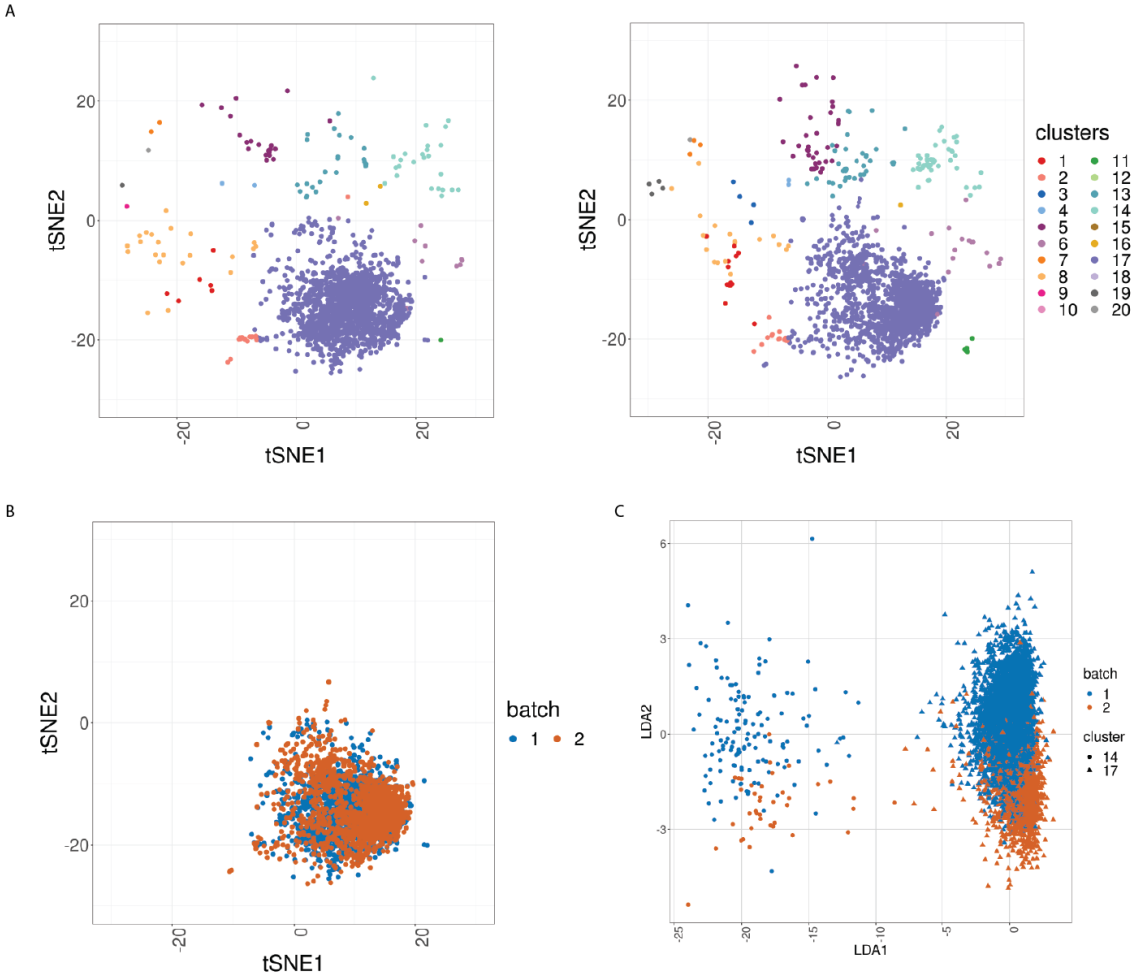
Supp. Fig. 1: Heatmap of the median lineage protein expression across clusters with the associated cluster percentages measured for all cells and all samples in the first dataset of samples from 3 CLL patients and 9 HC.



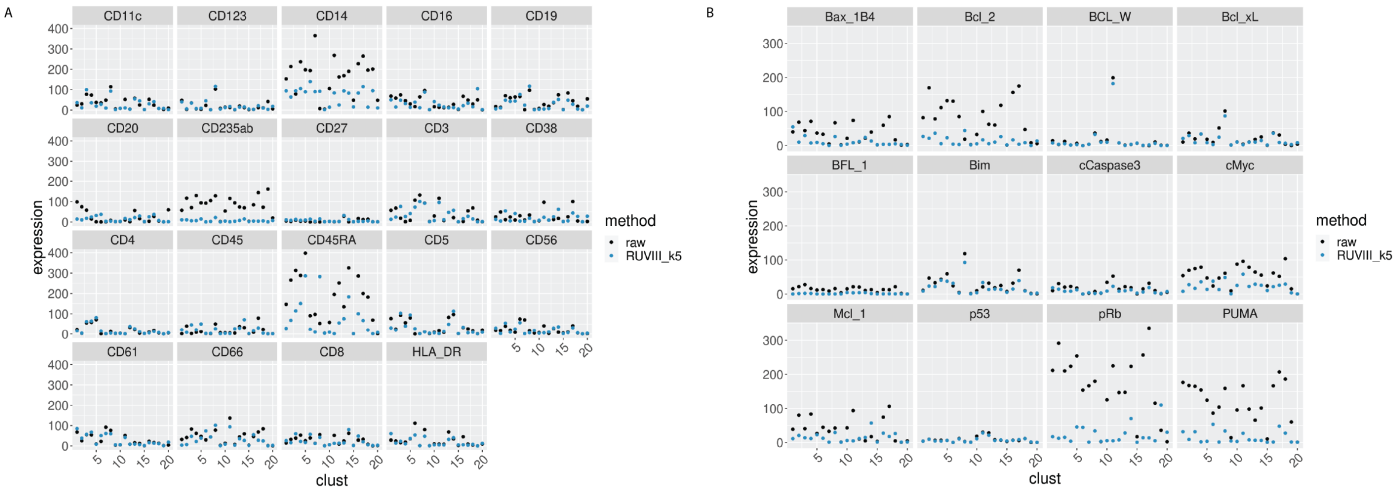
Supp. Fig. 2a: Proteins distribution for the samples CLL2 and HC1 before normalisation with k=5 across batch 1 and batch 2*. A) Lineage protein expression distributions for the sample CLL2 across batches, before normalisation. B) Same as A) with functional proteins. C) Lineage protein expression distributions for the sample HC1 across batches, before normalisation. D) Same as C) with functional proteins.*



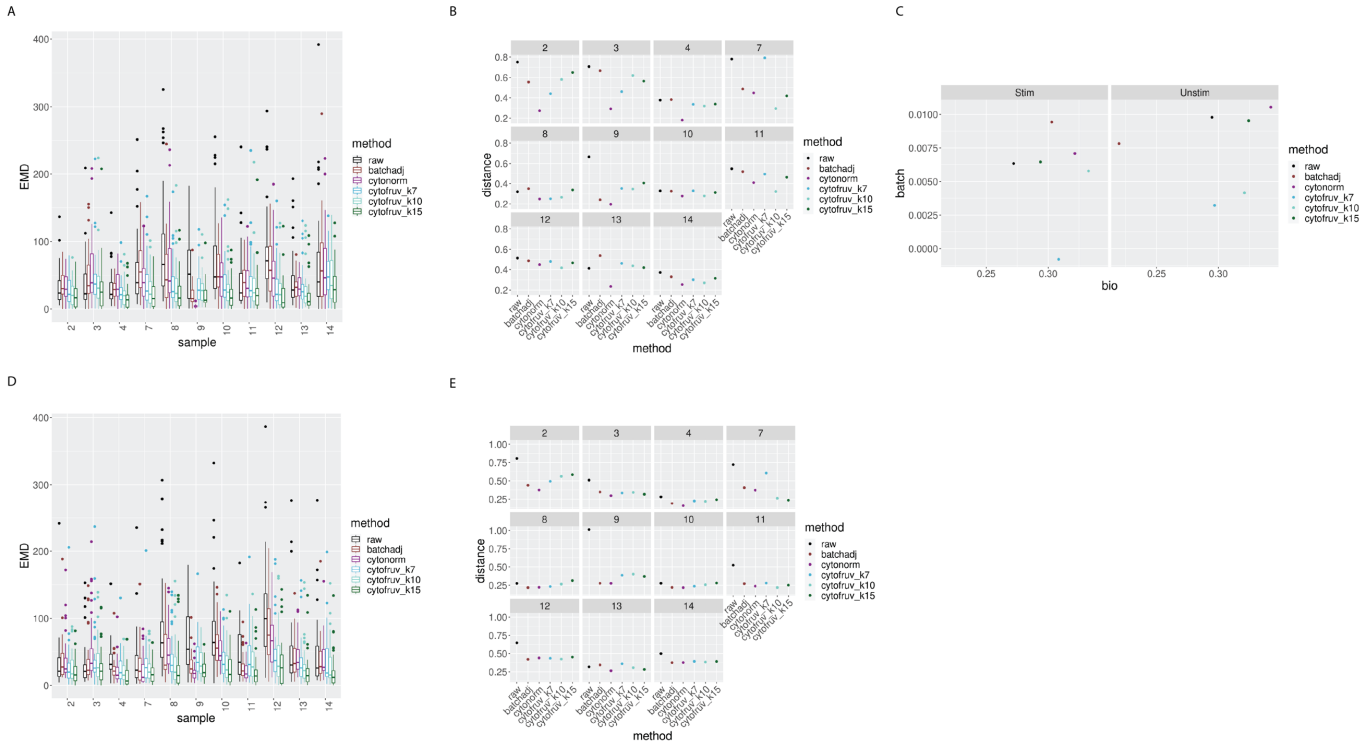
Supp. Fig. 2b: Proteins distributions for the samples CLL2 and HC1 after CytofRUV normalisation with k=5 across batch 1 and batch 2*. A) Lineage protein expression distributions for the CLL2 sample across batches, after CytofRUV normalisation. B) Same as A) with functional proteins. C) Lineage protein expression distributions for the sample HC1 across batches, after CytofRUV normalisation. D) Same as C) with functional proteins.*



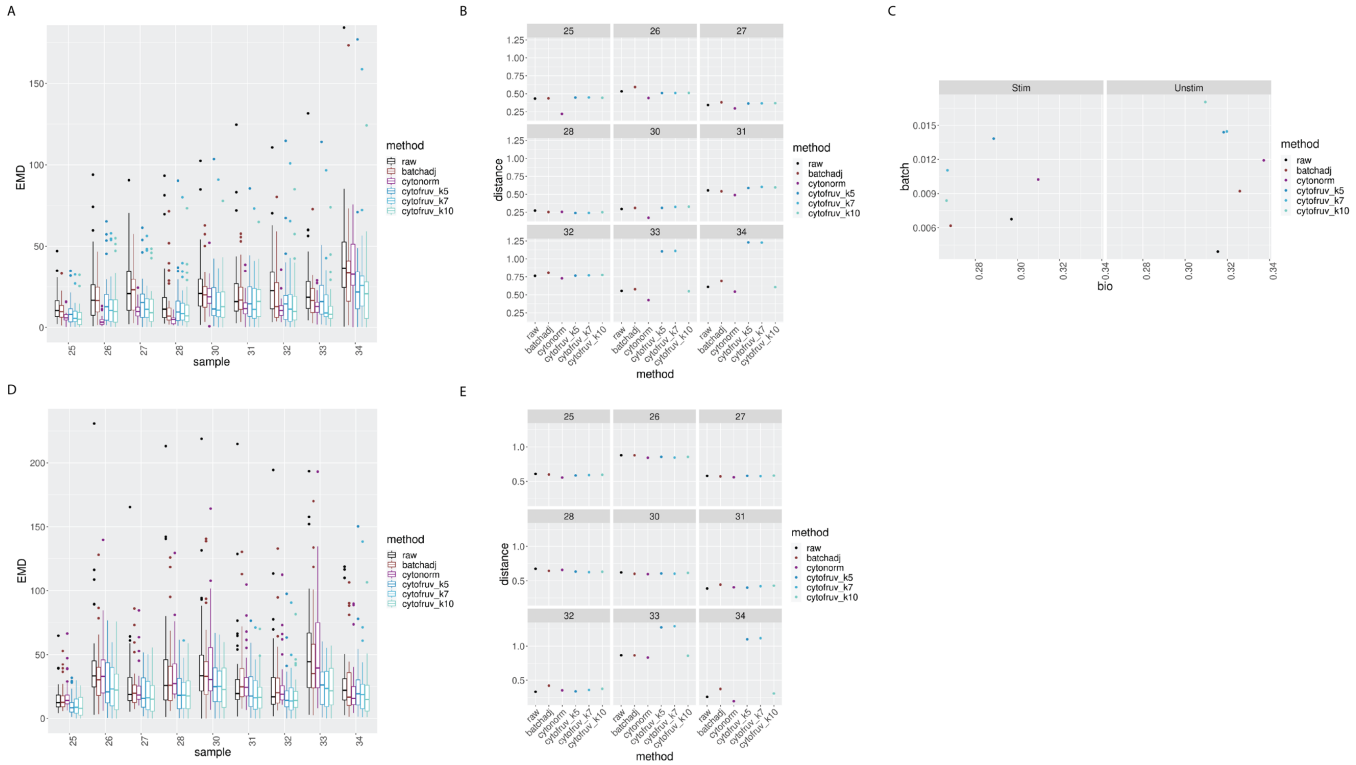
Supp. Fig. 3: Cell clustering plots to show batch effects effects in cells from the same cancer patient CLL1 sample replicated across 2 CyTOF runs after CytofRUV normalisation with k=5*. A) Same as Fig.3 A) after CytofRUV normalisation. B) Same as A) but coloured by batch**. C) Same as Fig.3 C) after CytofRUV normalisation.*



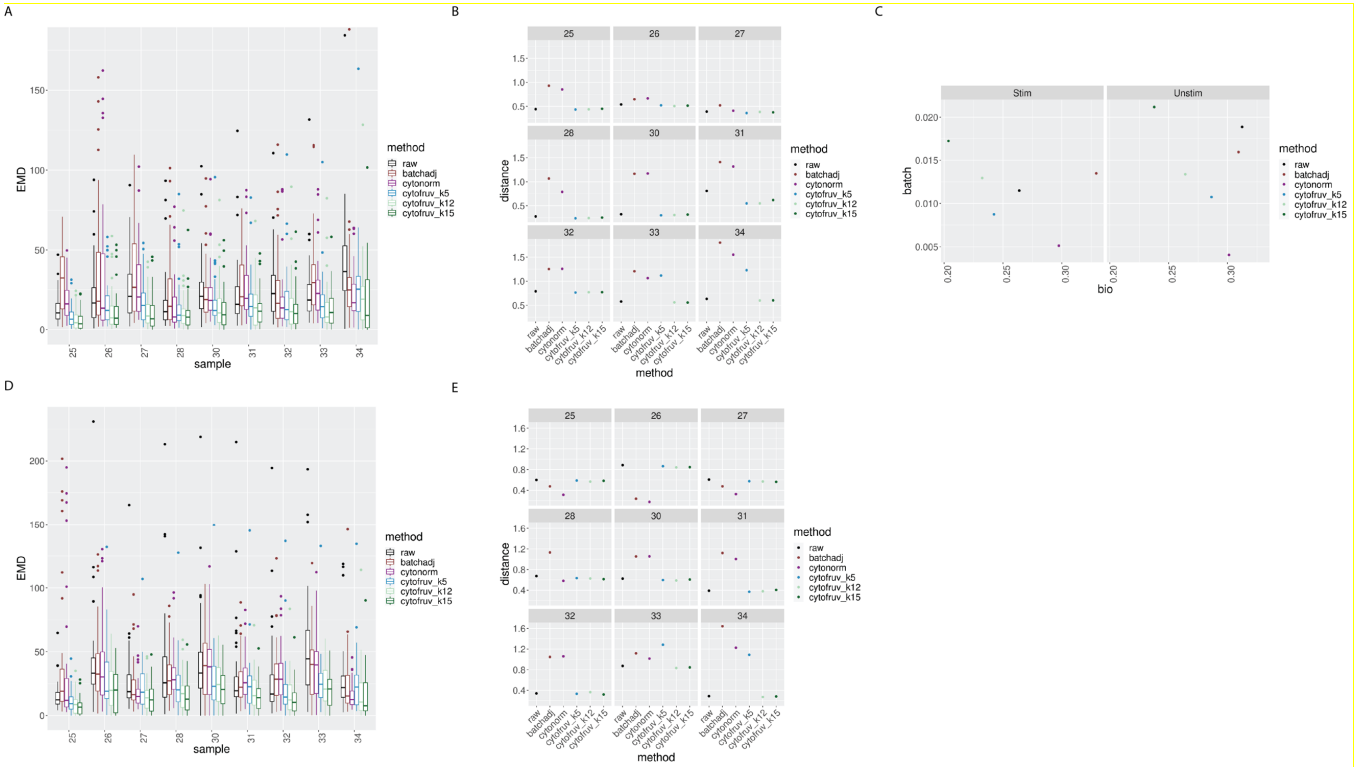
Supp. Fig. 4: EMD for all the proteins by cluster, before and after CytofRUV normalisation of the CLL2 sample, k=5*. A) EMD for lineage proteins by cluster before (black) and after CytofRUV normalisation (blue). B) Same as A), with functional proteins.*



Supp Fig. 5: Metrics to assess the effectiveness of the normalisation methods on the BatchAdjust dataset*. In all panels, the colour indicates either the raw data or the method used for normalisation. A) Boxplots of the Earth Movers Distance (EMD) between paired protein expression distributions for each batch's stimulated sample compared to that in the first batch. B) Hellinger distances between paired cell subpopulation proportions for each batch's stimulated sample compared to that in the first batch. C) Mean silhouette scores computed for all stimulated and unstimulated samples with those for cell subpopulations (bio) on the x-axis and for batch (batch) on the y-axis. D) Same as A) for the unstimulated samples. E) Same as B) for the unstimulated samples.*



Supp Fig. 6: Metrics to assess the effectiveness of the normalisation methods on samples 2 from the CytoNorm dataset using stimulated samples 2 as replicated reference samples*. In all panels, the colour indicates either the raw data or the method used for normalisation. A) Boxplots of the Earth Movers Distance (EMD) between paired protein expression distributions for each batch's stimulated sample across compared to that in the first batch. B) Hellinger distances between paired cell subpopulation proportions for each batch's stimulated sample compared to that in the first batch. C) Mean silhouette scores computed for all stimulated and unstimulated samples with those for cell subpopulations (bio) on the x-axis and for batch (batch) on the y-axis. D) Same as A) for the unstimulated samples. E) Same as B) for the unstimulated samples.*



Supp Fig. 7: Metrics to assess the effectiveness of the normalisation methods on samples 2 from the CytoNorm dataset using both the stimulated and unstimulated samples 1 as replicated reference samples*. In all panels, the colour indicates either the raw data or the method used for normalisation. A) Boxplots of the Earth Movers Distance (EMD) between paired protein expression distributions for each batch's stimulated sample across compared to that in the first batch. B) Hellinger distances between paired cell subpopulation proportions for each batch's stimulated sample compared to that in the first batch. C) Mean silhouette scores computed for all stimulated and unstimulated samples with those for cell subpopulations (bio) on the x-axis and for batch (batch) on the y-axis. D) Same as A) for the unstimulated samples. E) Same as B) for the unstimulated samples.*

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